



Towards an Optimal Noise Versus Resolution Trade-off in Wind Scatterometry

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IOWVST Meeting Utrecht Netherlands

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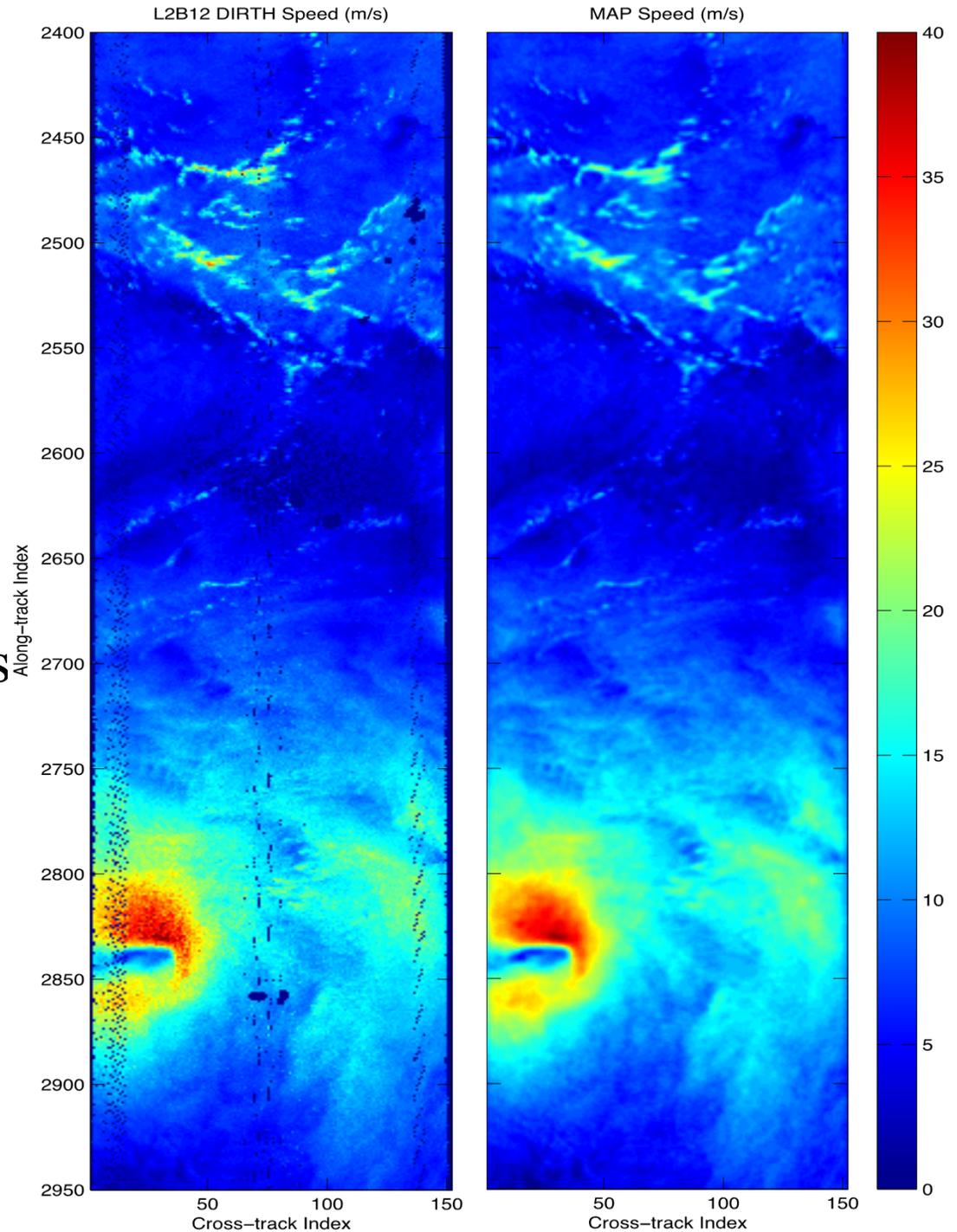
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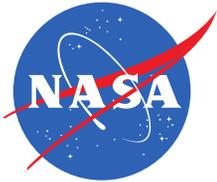
The work described in this paper was carried out by the Jet Propulsion Laboratory, California Institute of Technology under a contract with the National Aeronautics and Space Administration



Overview

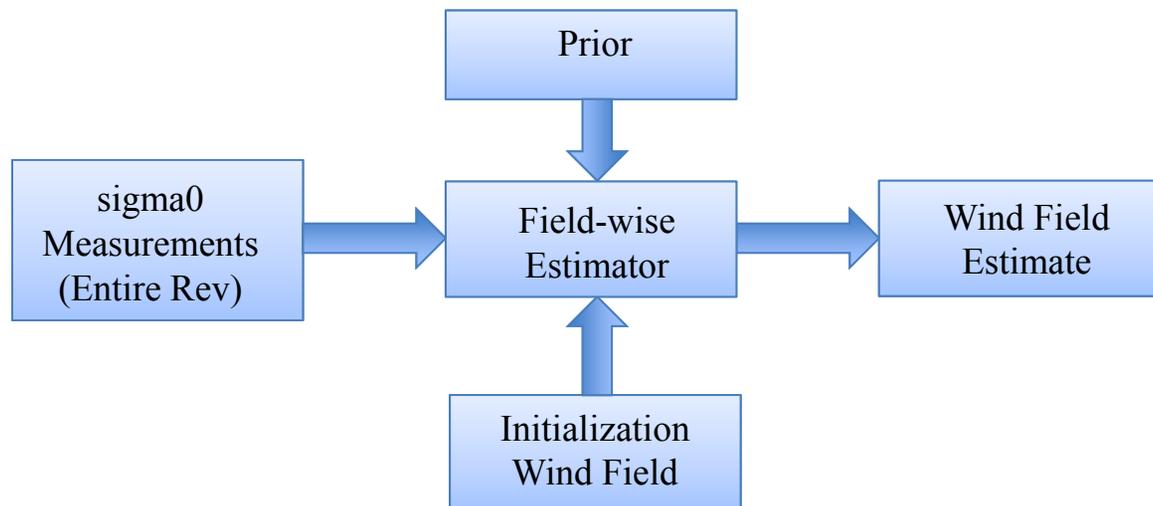
- Estimation approach
 - Field-wise estimation with statistical signal model
- Implementation
 - MAP estimation
 - Development of priors
- Analysis (QSCAT)
 - Speed histograms
 - Metrics vs. ECMWF
 - Spectra
 - Examples





Estimation Approach

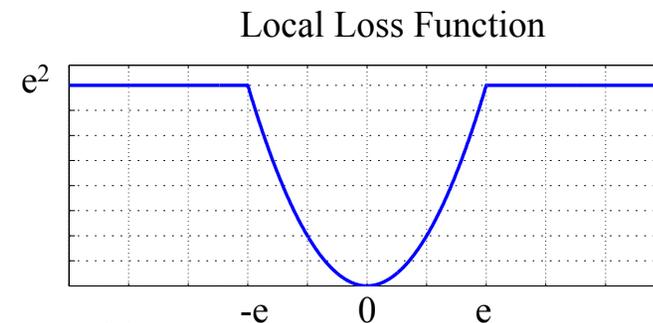
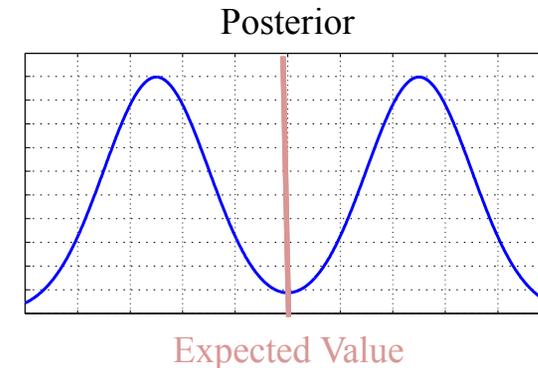
- Field-wise retrieval with statistical signal model (i.e., prior)
 - Simultaneously estimate every WVC for entire rev
 - Prior incorporates spatial covariance (k^{-2} spectrum)
 - No ambiguity removal post wind-retrieval
 - Effectively done by initialization





Estimation Approach

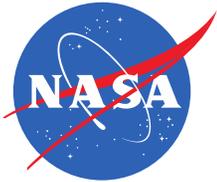
- Bayes Estimation
 - Multimodal => local quadratic loss
 - Impractical to implement unless local ball $\rightarrow 0$
 - Converges to the MAP estimate
- MAP Estimation
 - Practical to implement
 - Incorporates the spatial structure of prior
 - Trades off noise and resolution
 - May be biased



Maximize log of posterior distribution (gradient search)

$$\frac{\partial}{\partial \vec{U}(x)} \log f(\vec{U}(x) | \vec{\sigma}_m^0) = \frac{\partial}{\partial \vec{U}(x)} [\log f(\vec{\sigma}_m^0 | \vec{U}(x)) + \log f(\vec{U}(x))]$$

ML portion Prior



Implementation: MAP Estimation

- ML portion (left side)^[1]

$$\frac{\partial}{\partial U_i(x)} \log f(\vec{\sigma}_m^0 | \vec{U}(x)) = \sum_n -K_n A_n(x) \frac{\partial \text{gmf}_n(\vec{U}(x))}{\partial U_i(x)}$$

- Prior indep Gaussian with spatial cov matrices^[2]

$$f(\vec{U}(x)) = f(U_s(x))f(U_d(x))$$

If signal covariance model is stationary, can be implemented as convolutions (fast computation with FFT)

$$\frac{\partial \log f(U_s(x))}{\partial U_s(x)} = \frac{-1}{2} \mathbf{R}_s^{-1} (U_s(x) - \mu_s(x))$$

$$\frac{\partial \log f(U_d(x))}{\partial U_d(x)} = \sin(U_d(x)) \circ \mathbf{R}_d^{-1} \cos(U_d(x)) - \cos(U_d(x)) \circ \mathbf{R}_d^{-1} \sin(U_d(x))$$

[1] B. A. Williams and D. G. Long, "A reconstruction approach to scatterometer wind vector field retrieval," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 49, no. 6, pp. 1850 – 1864, June 2011.

[2] B. A. Williams, "A field-wise retrieval approach to the noise versus resolution trade-off in wind scatterometry," *IEEE Transactions on Geoscience and Remote Sensing*, to be submitted.



Implementation: Prior Covariance

- Exponential covariance function

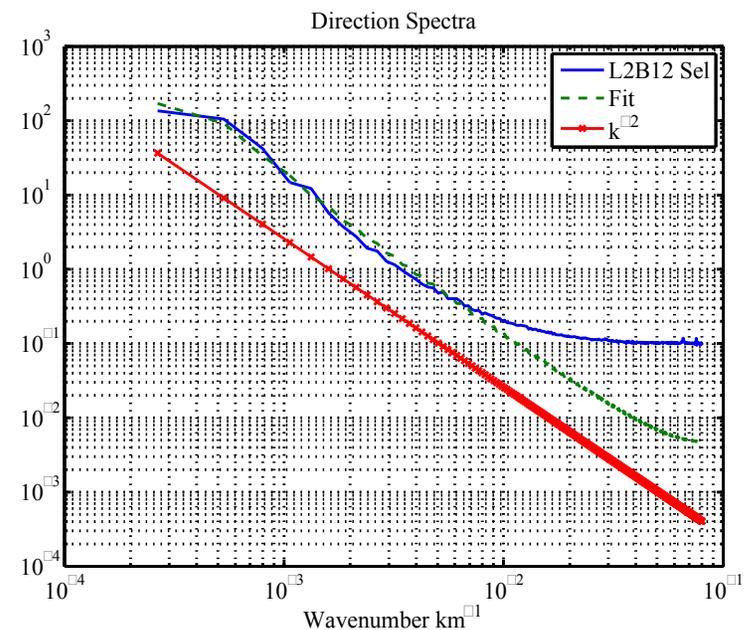
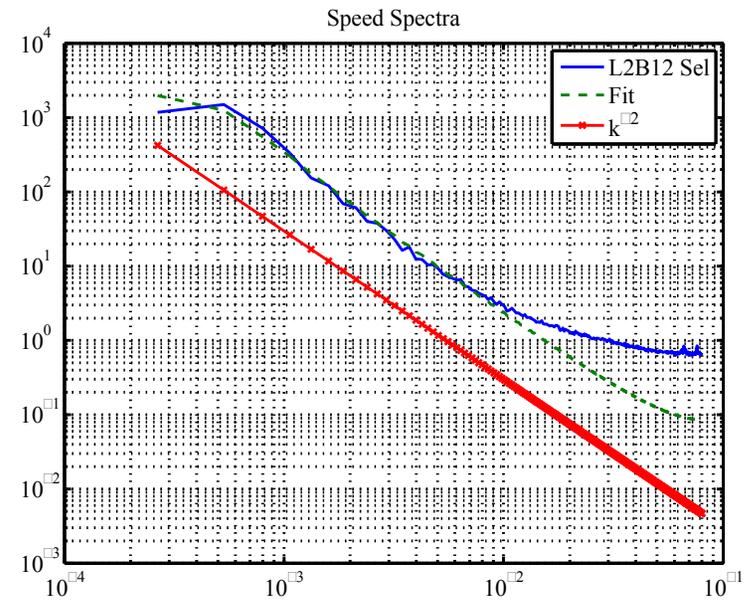
$$c(x) = e^{-2\pi k_0 |x|} \quad \mathcal{F}\{c(x)\} = \frac{2k_0}{k^2 + k_0^2}$$

- Estimate parameters from L2B12 Selected ambiguity using signal and noise model (direction cov of $\psi = e^{id}$)

$$\text{cov}(x) = ae^{-b|x|} + c\delta(x)$$

TABLE I
ESTIMATED MODEL PARAMETERS

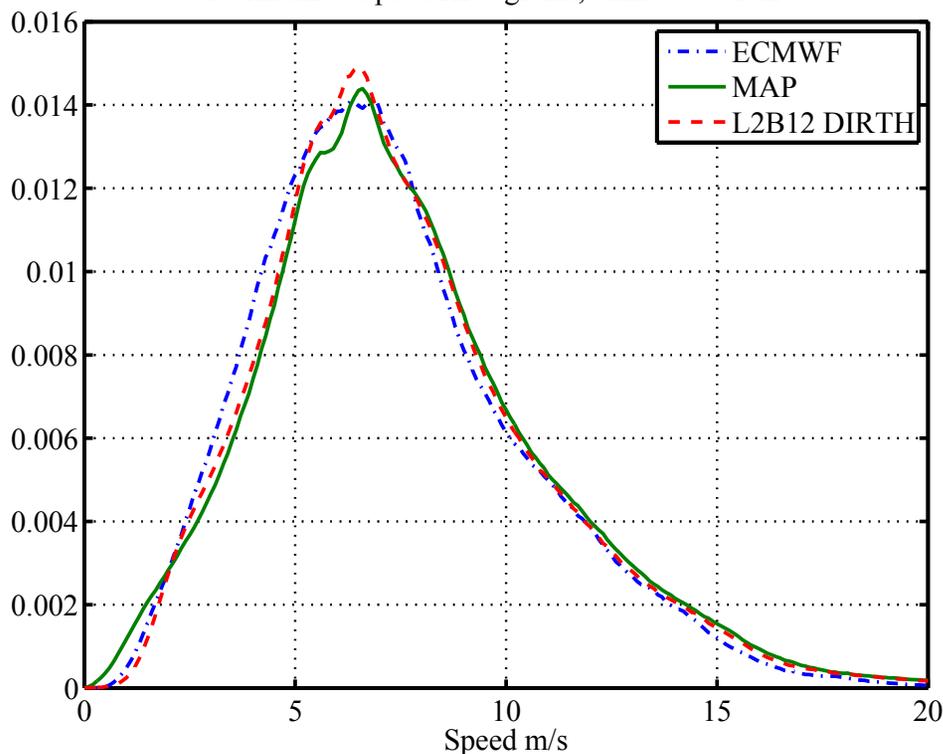
Parameter	Value	
	Speed	Direction
a	12.58	0.924
b	0.01238	0.01029
c	0.678	0.074



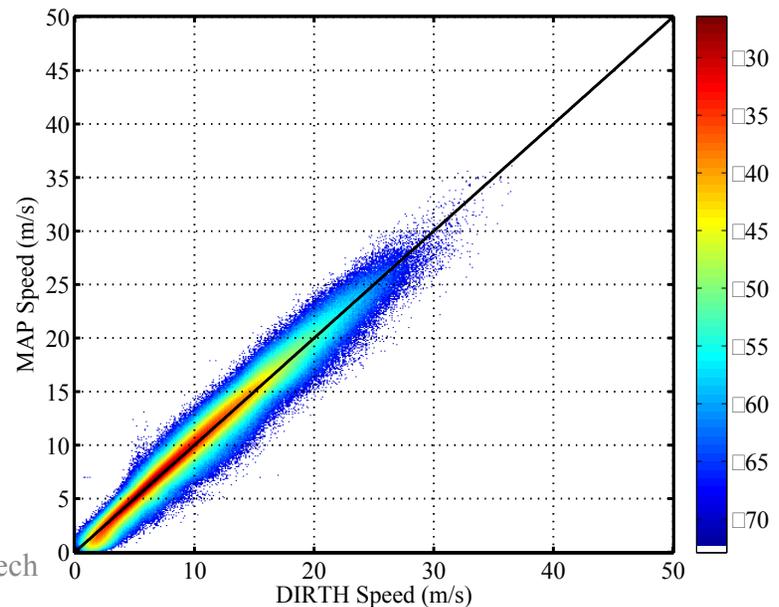
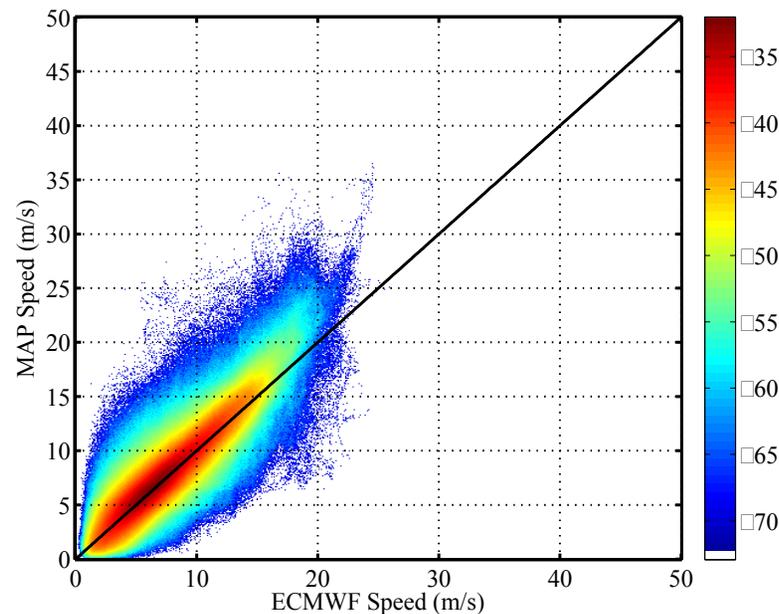


Analysis: Speed Histograms

Normalized Speed Histograms, binned at 0.1 m/s

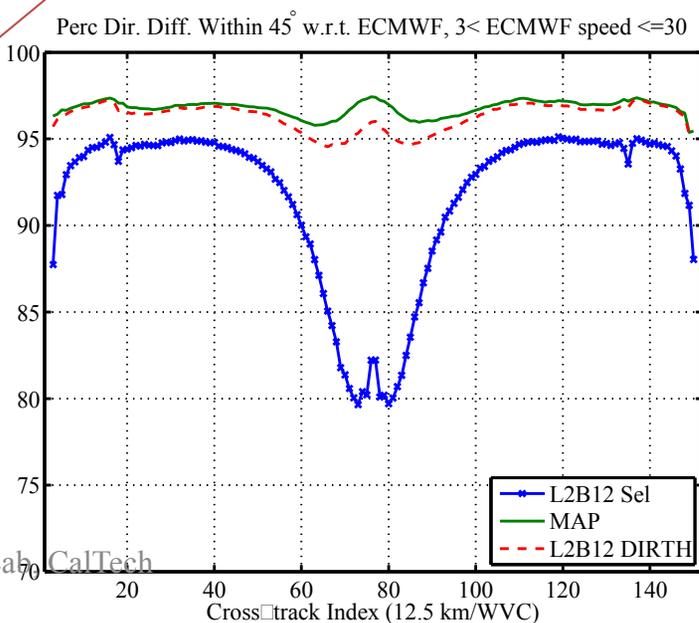
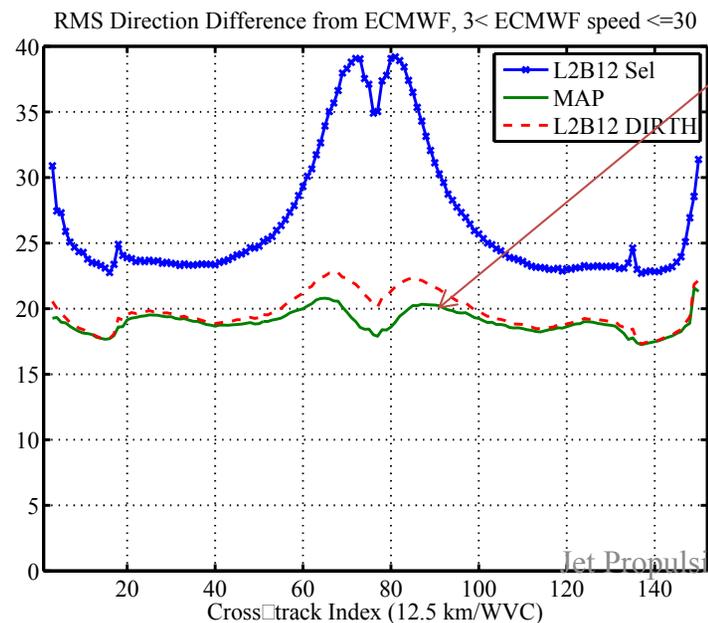
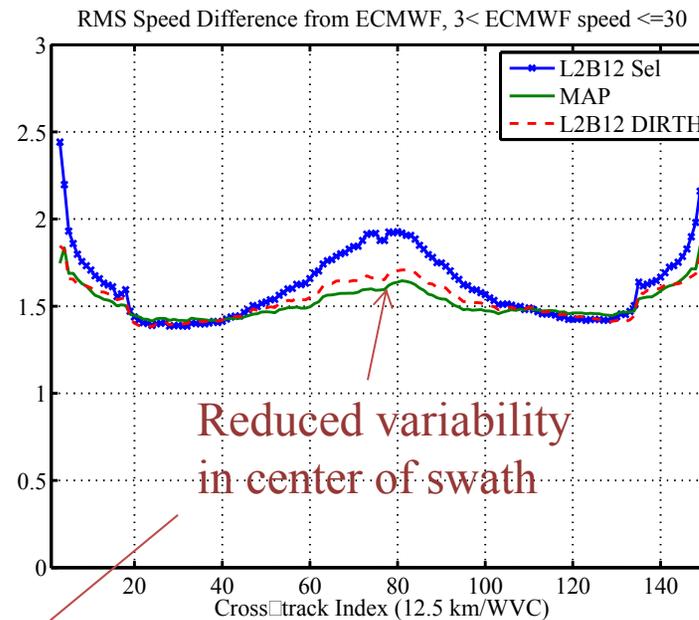
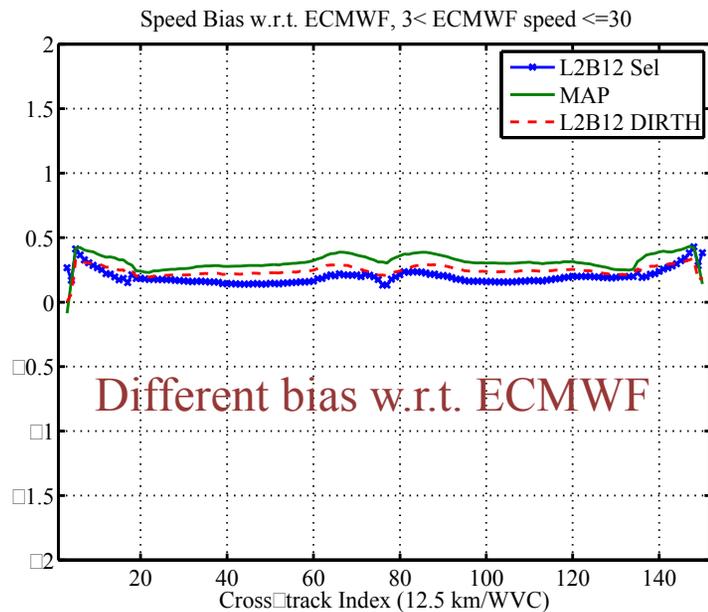


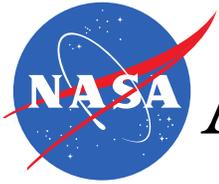
- 99 QSCAT Revs: 49663-49762
- MAP speed consistent with L2B12 DIRTH, but low speeds are biased slightly lower



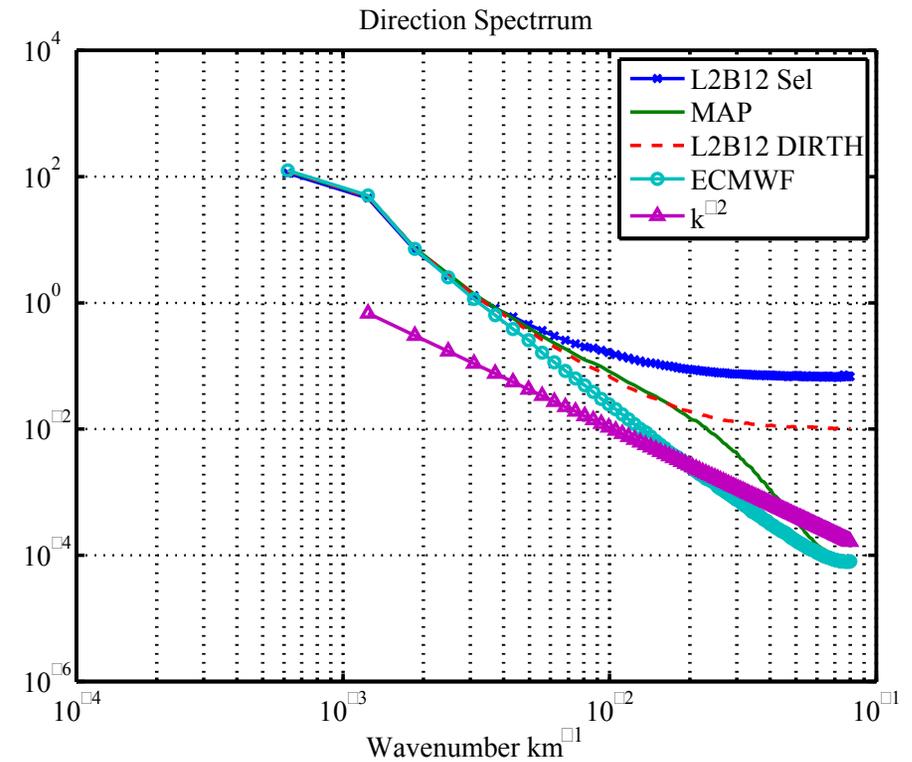
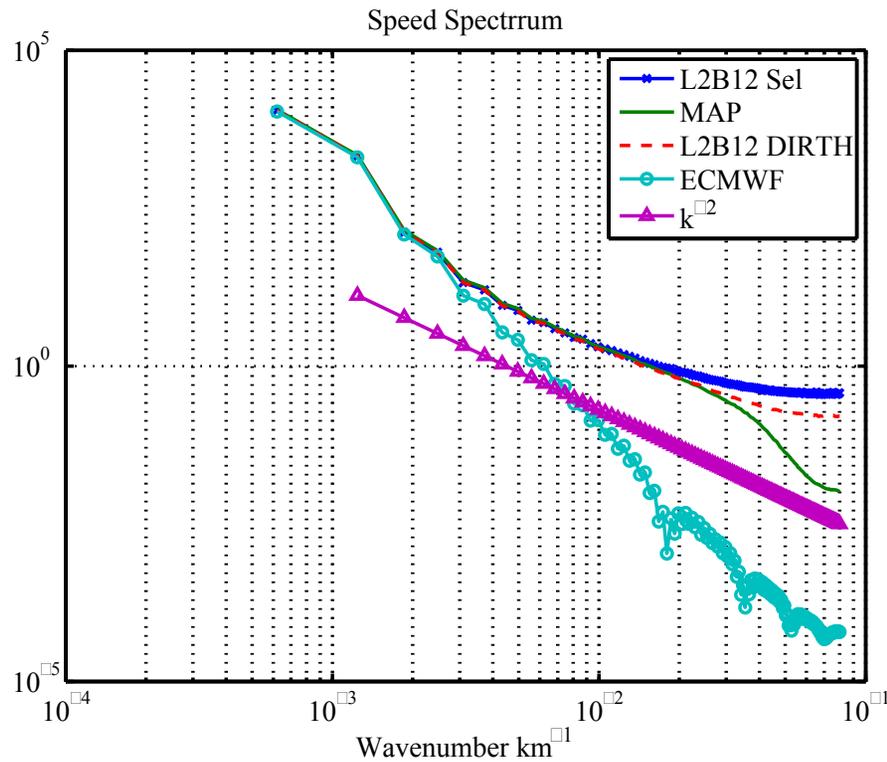


Analysis: Metrics w.r.t. ECMWF

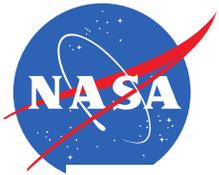




Analysis: Speed and Direction Spectra



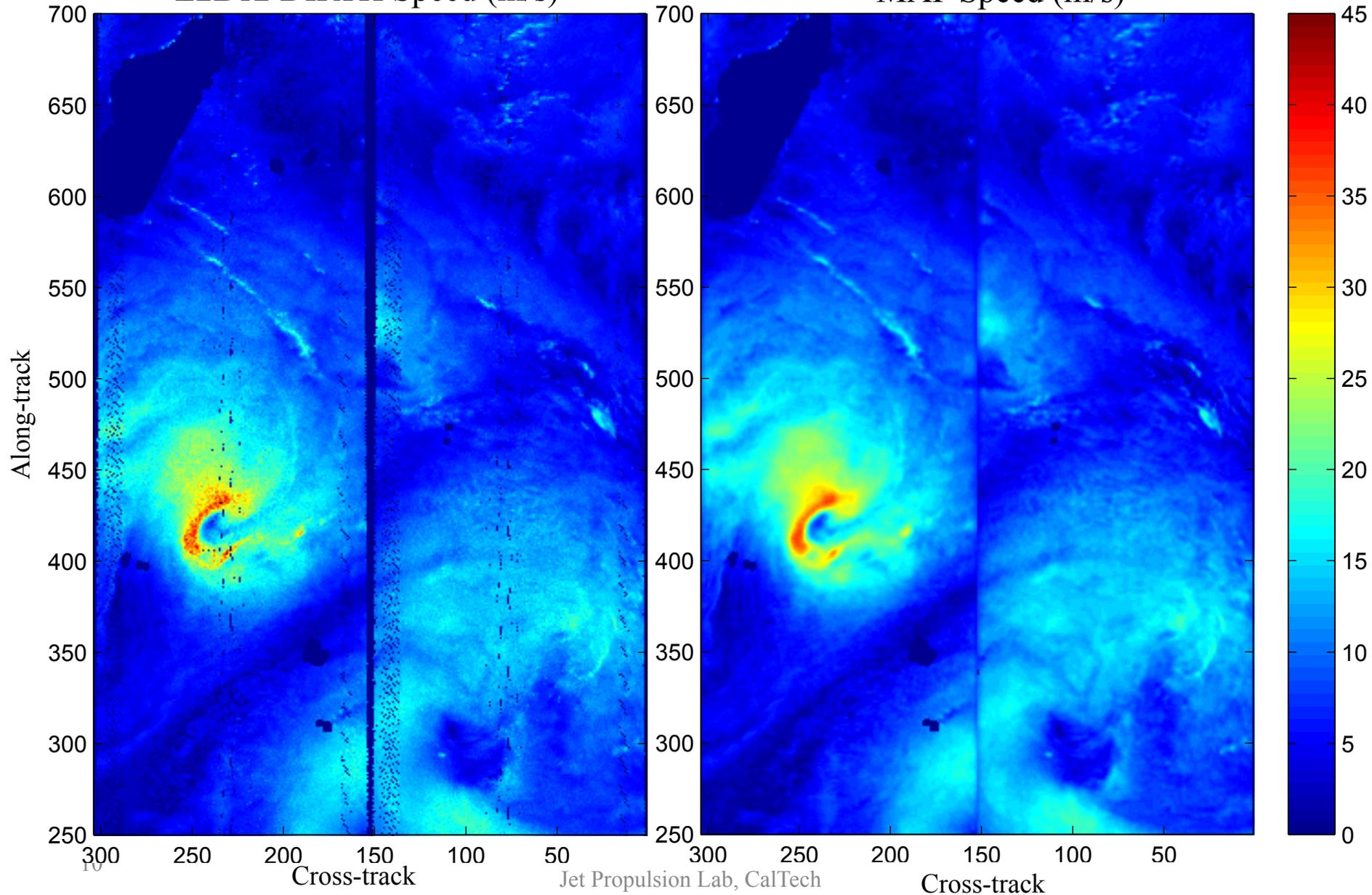
- Average speed resolution $\sim 25\text{-}33$ km
- Average direction resolution ~ 50 km



Examples: Tiled Revs

L2B12 DIRTH Speed (m/s)

MAP Speed (m/s)

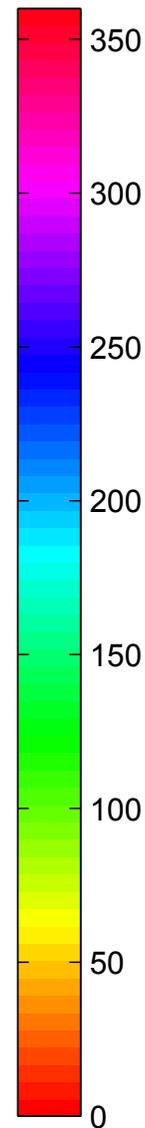
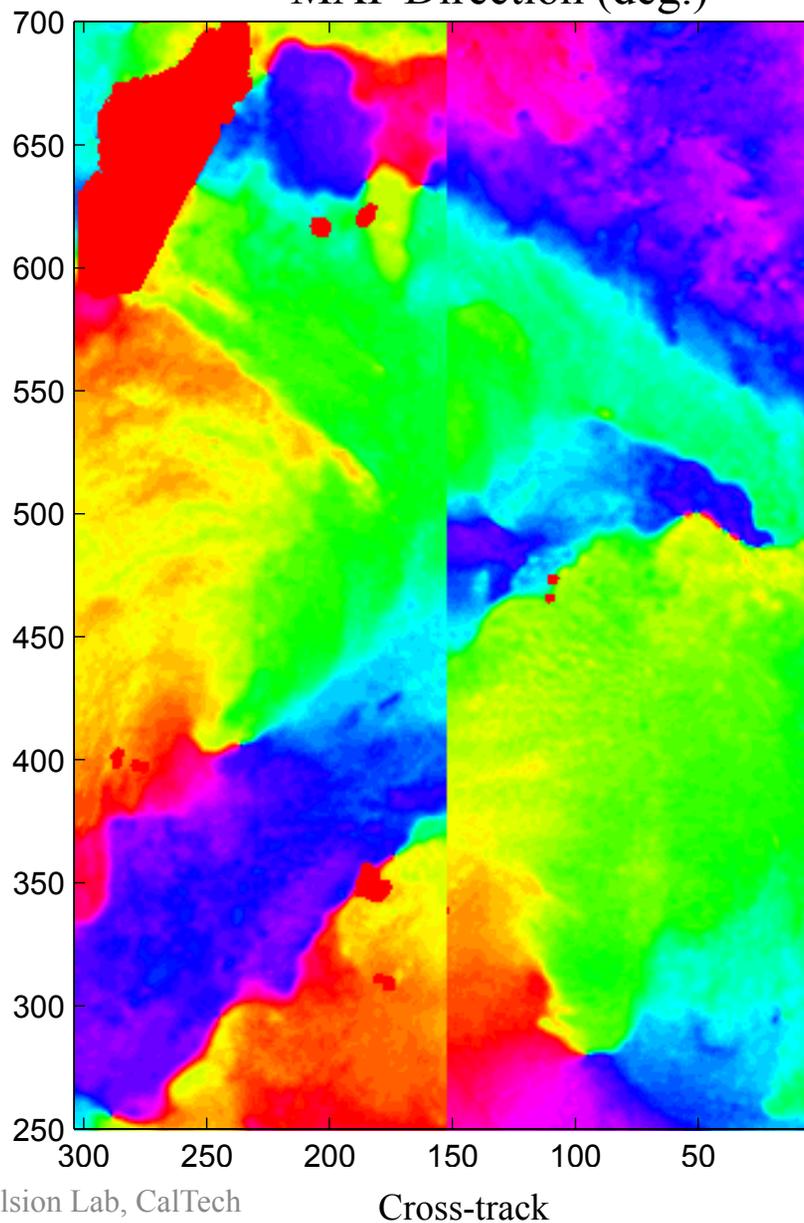
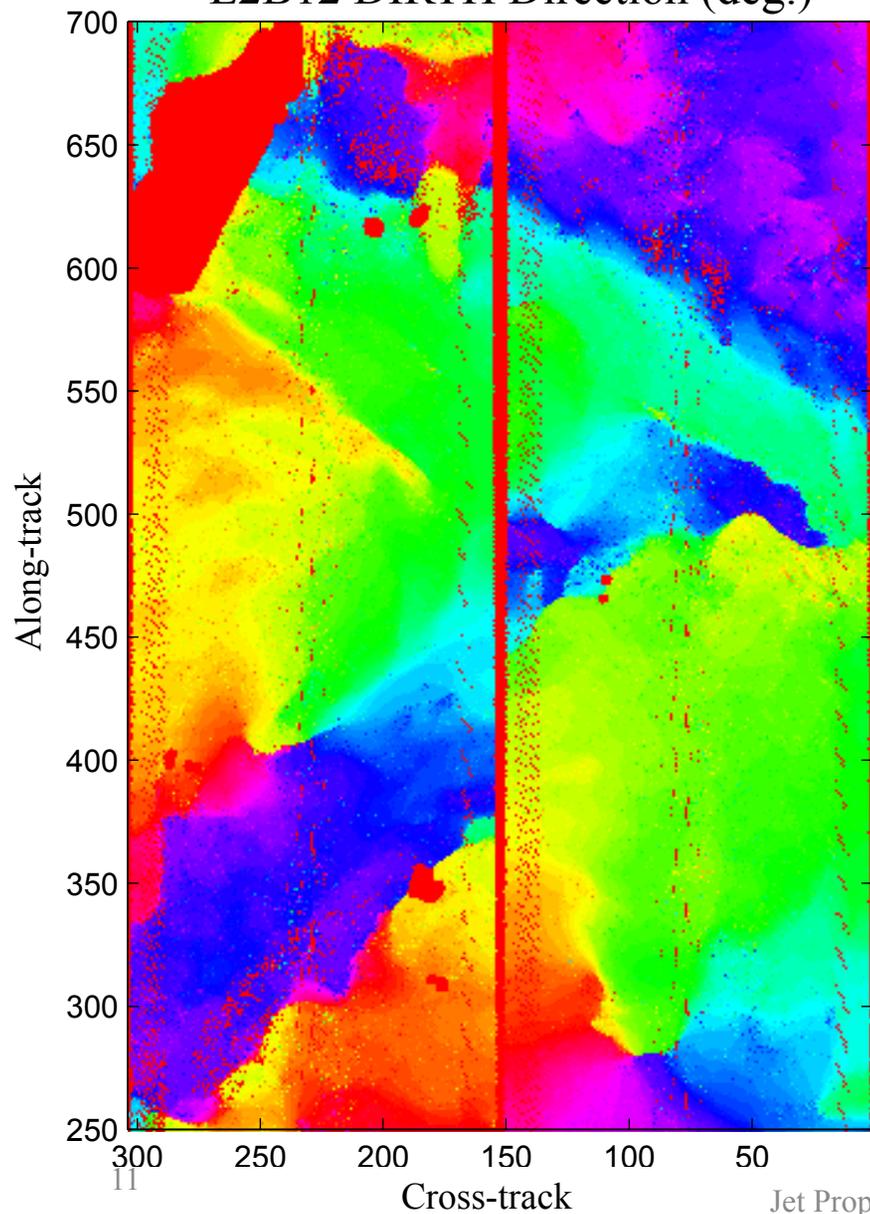


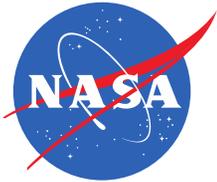


Examples: Tiled Revs

L2B12 DIRTH Direction (deg.)

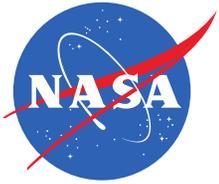
MAP Direction (deg.)





Conclusion

- MAP estimation with priors that incorporate spatial structure
 - Outperforms DIRTH in all metrics except speed bias w.r.t. ECMWF
 - Automatically filters (attenuates) signal components that are expected to be noisy
 - Only parameters to tune (given a prior) are Kp_m , WVC posting, and numeric gradient search parameters (i.e., step size, max iterations, and initialization)
- This methodology may be applied to improve several special applications
 - Special priors for hurricanes, fronts, or other storm features
 - Wind and rain estimation with rain priors
 - Coastal and ice-edge applications (can handle σ_0 from mixed surfaces)

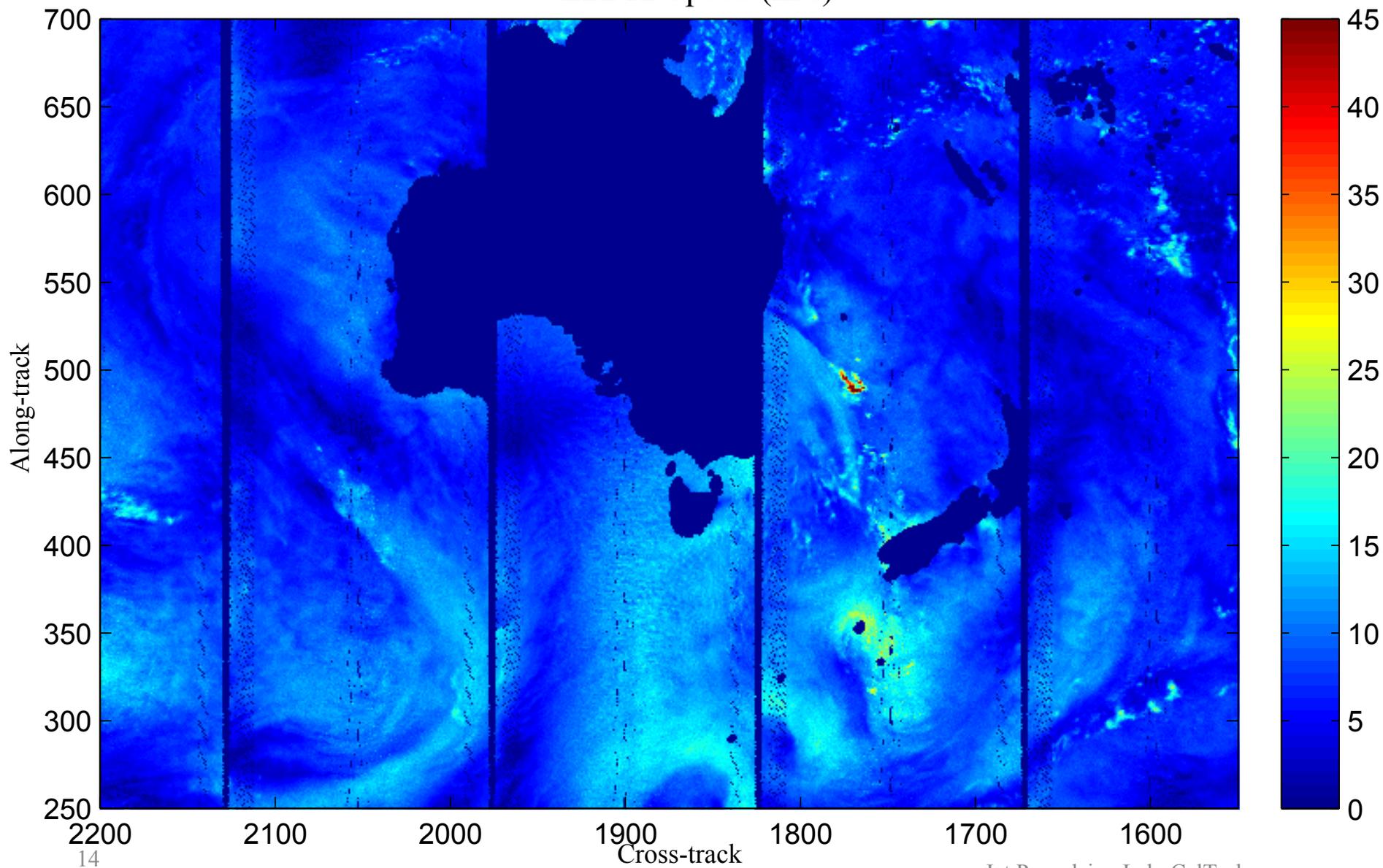


Backup Slides



Examples: Tiled Revs

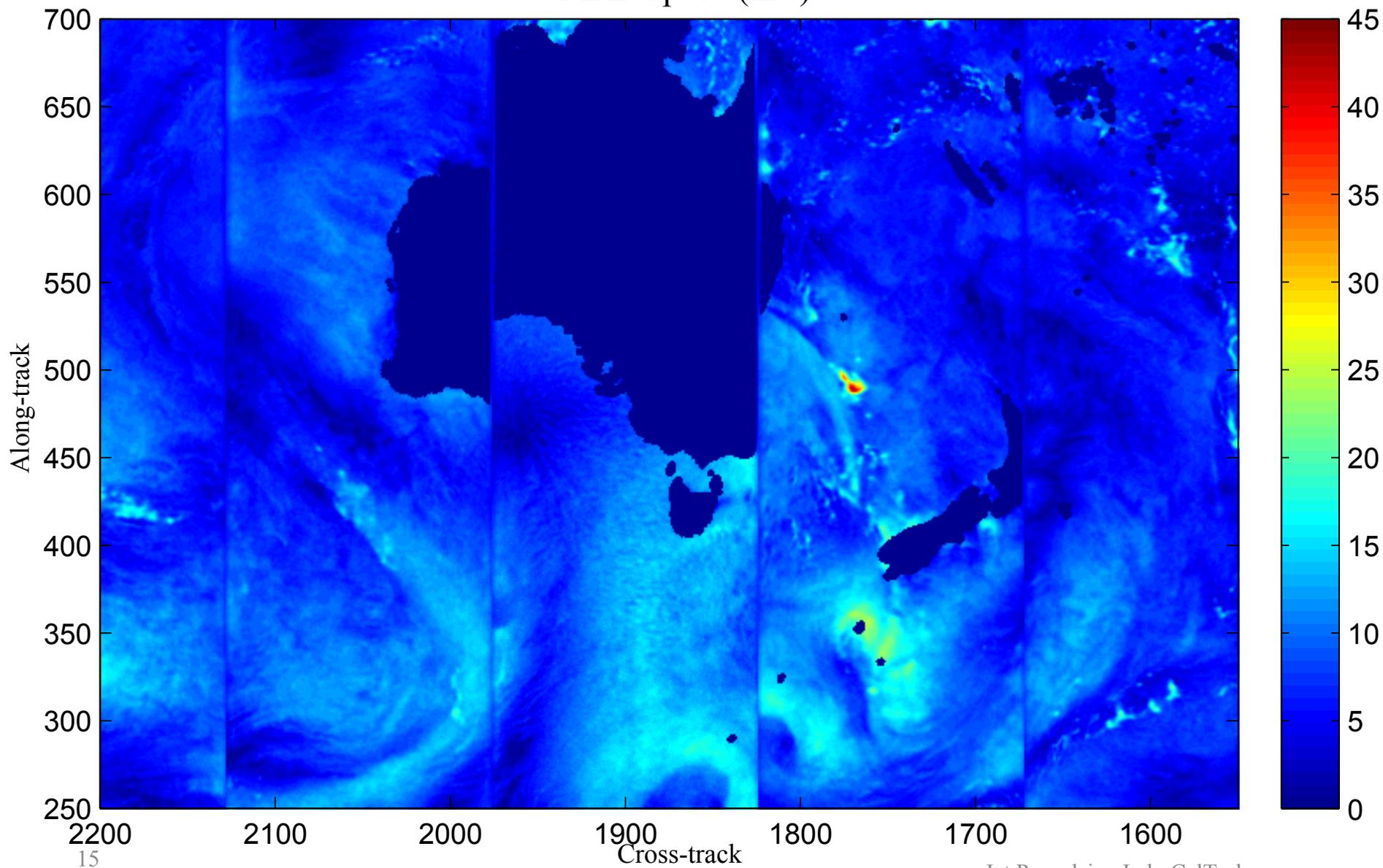
L2B12 Speed (m/s)





Examples: Tiled Revs

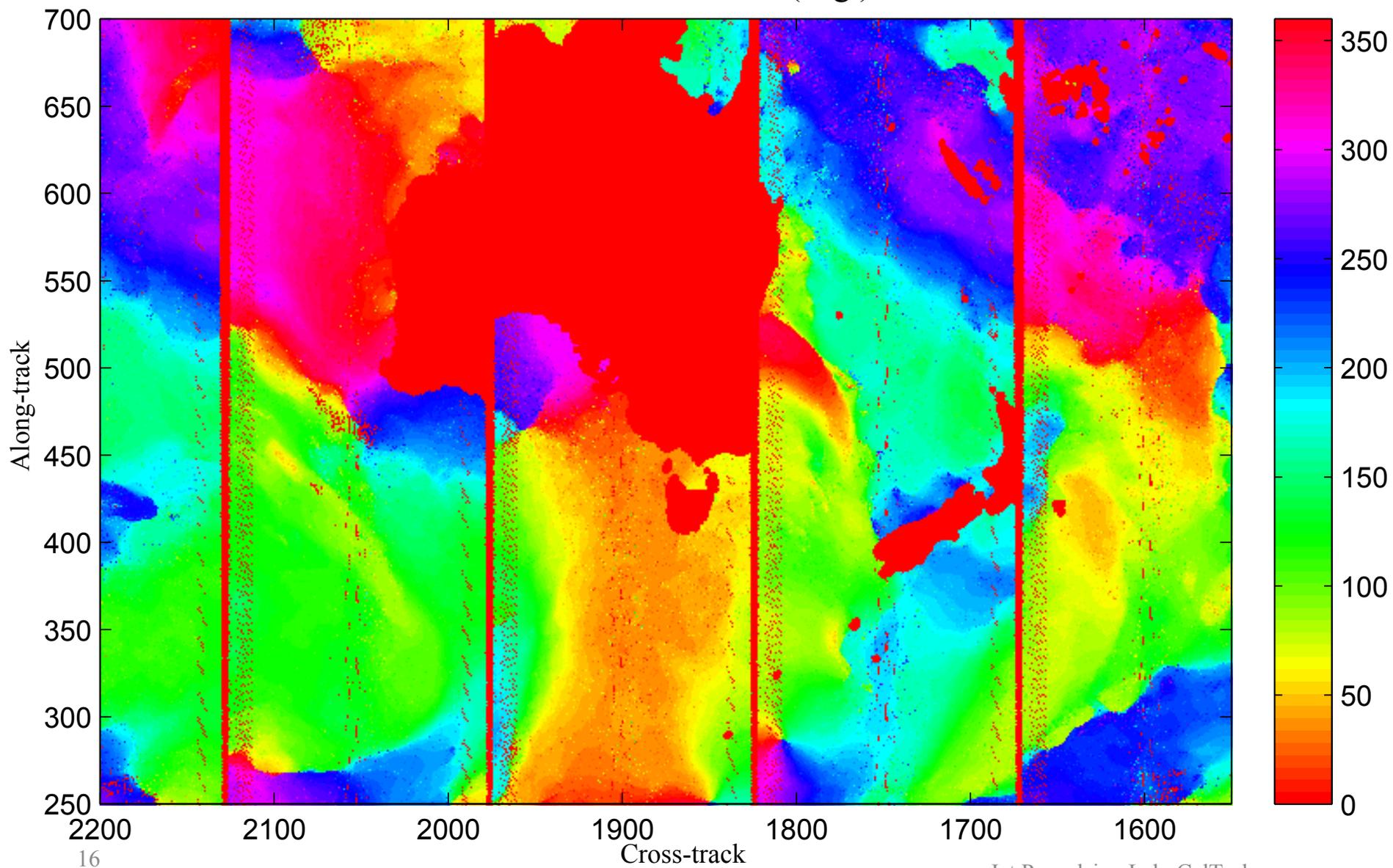
MAP Speed (m/s)





Examples: Tiled Revs

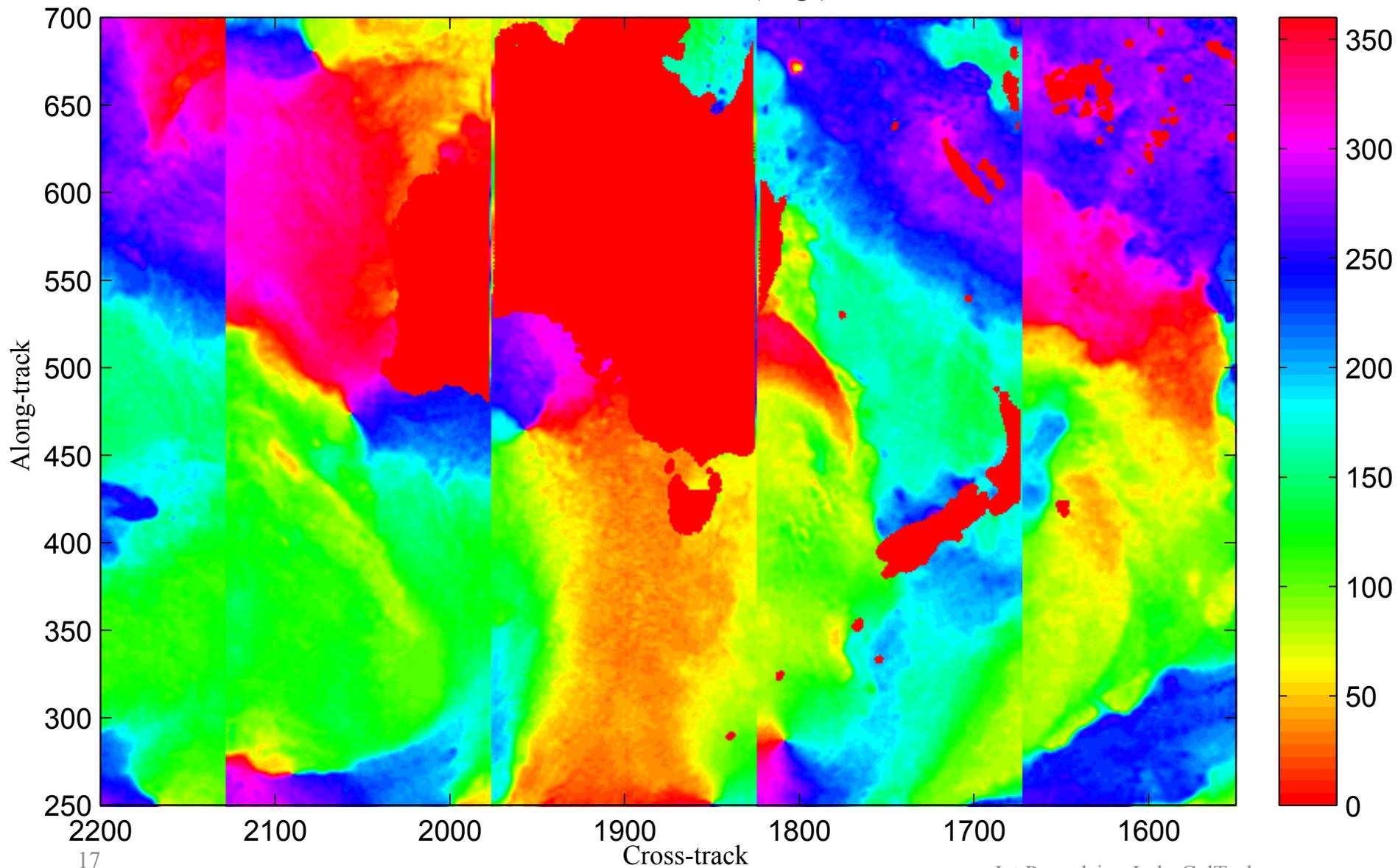
L2B12 Direction (deg.)





Examples: Tiled Revs

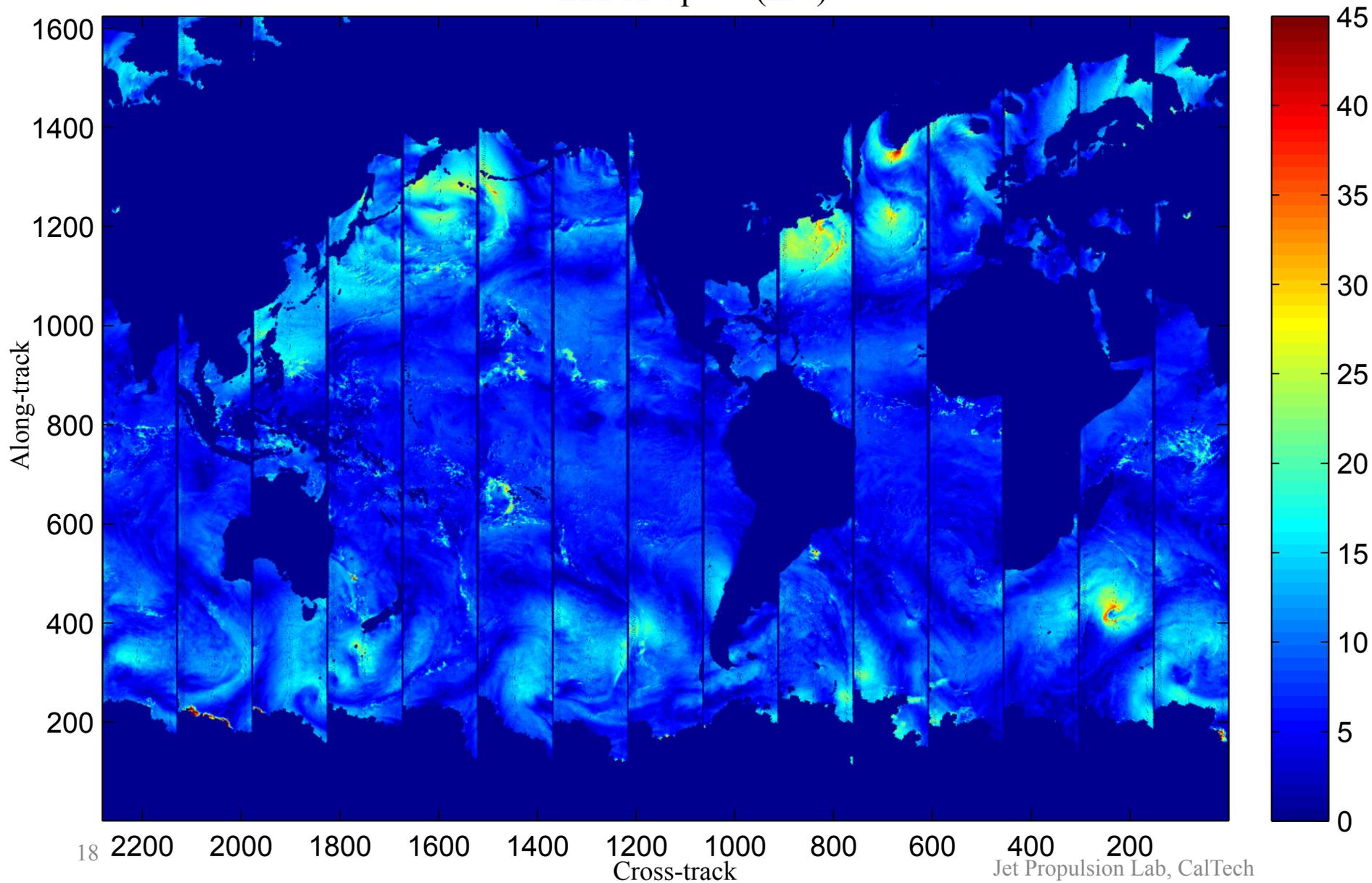
MAP Direction (deg.)





Examples: Tiled Revs

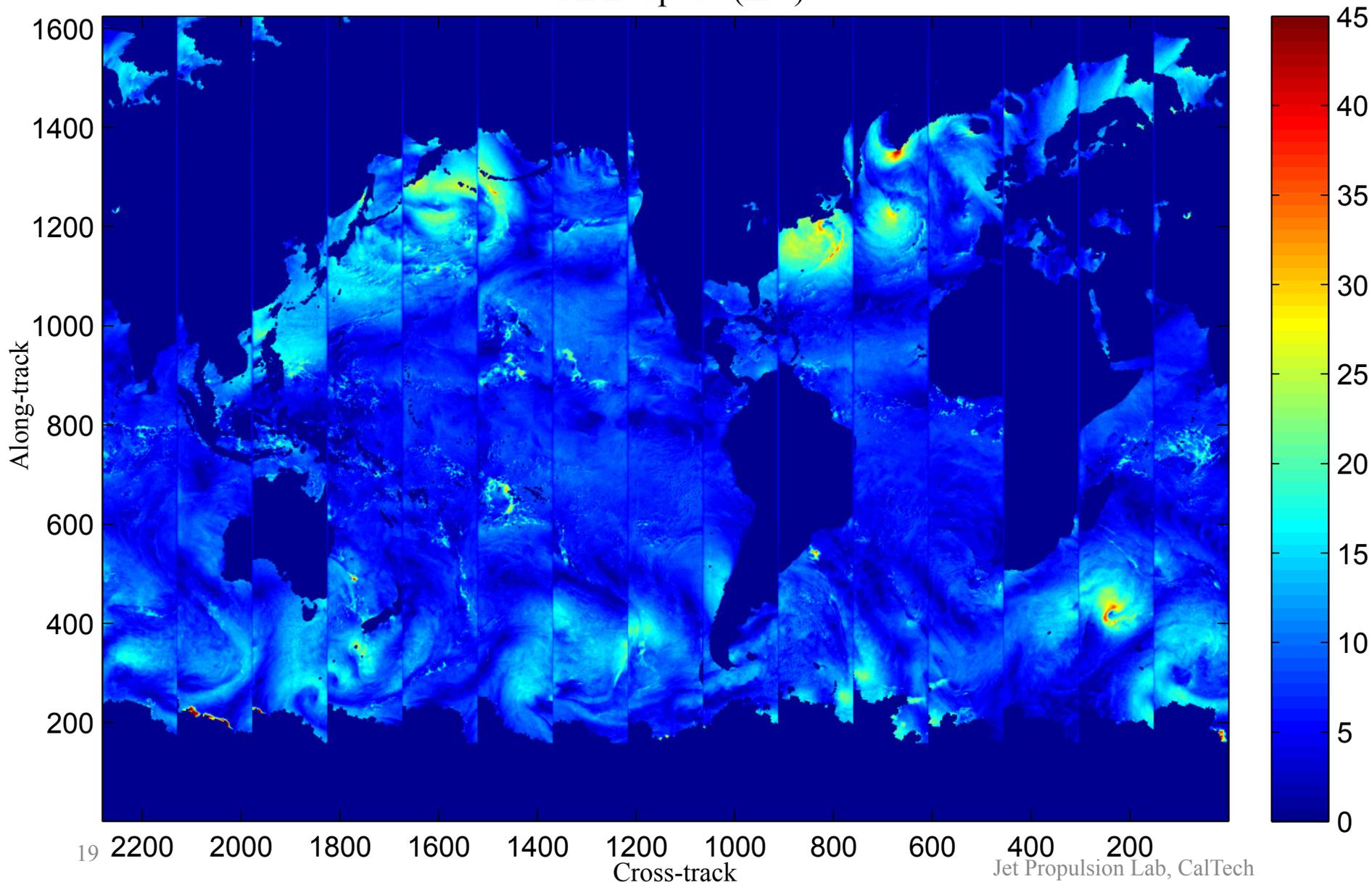
L2B12 Speed (m/s)





Examples: Tiled Revs

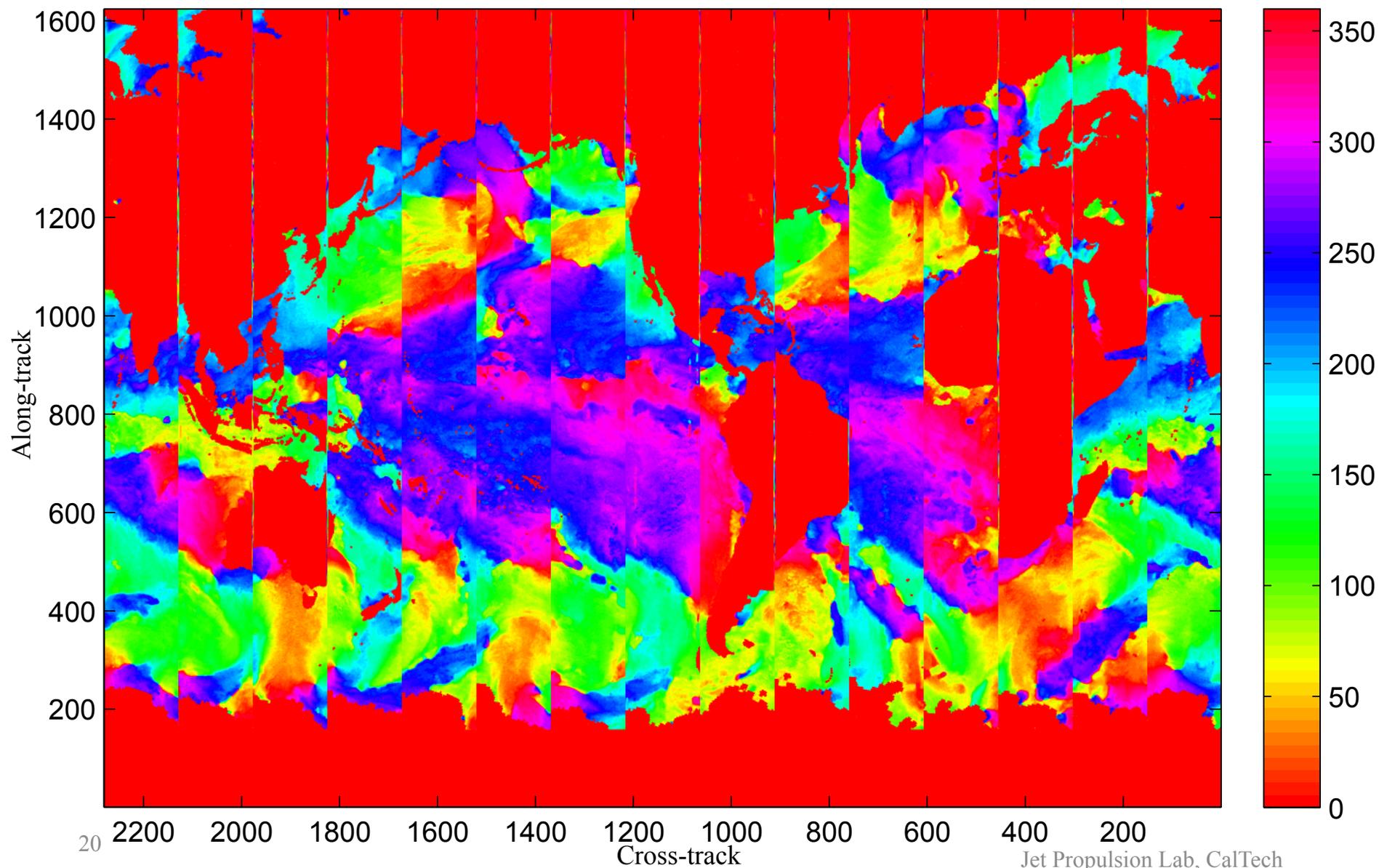
MAP Speed (m/s)





Examples: Tiled Revs

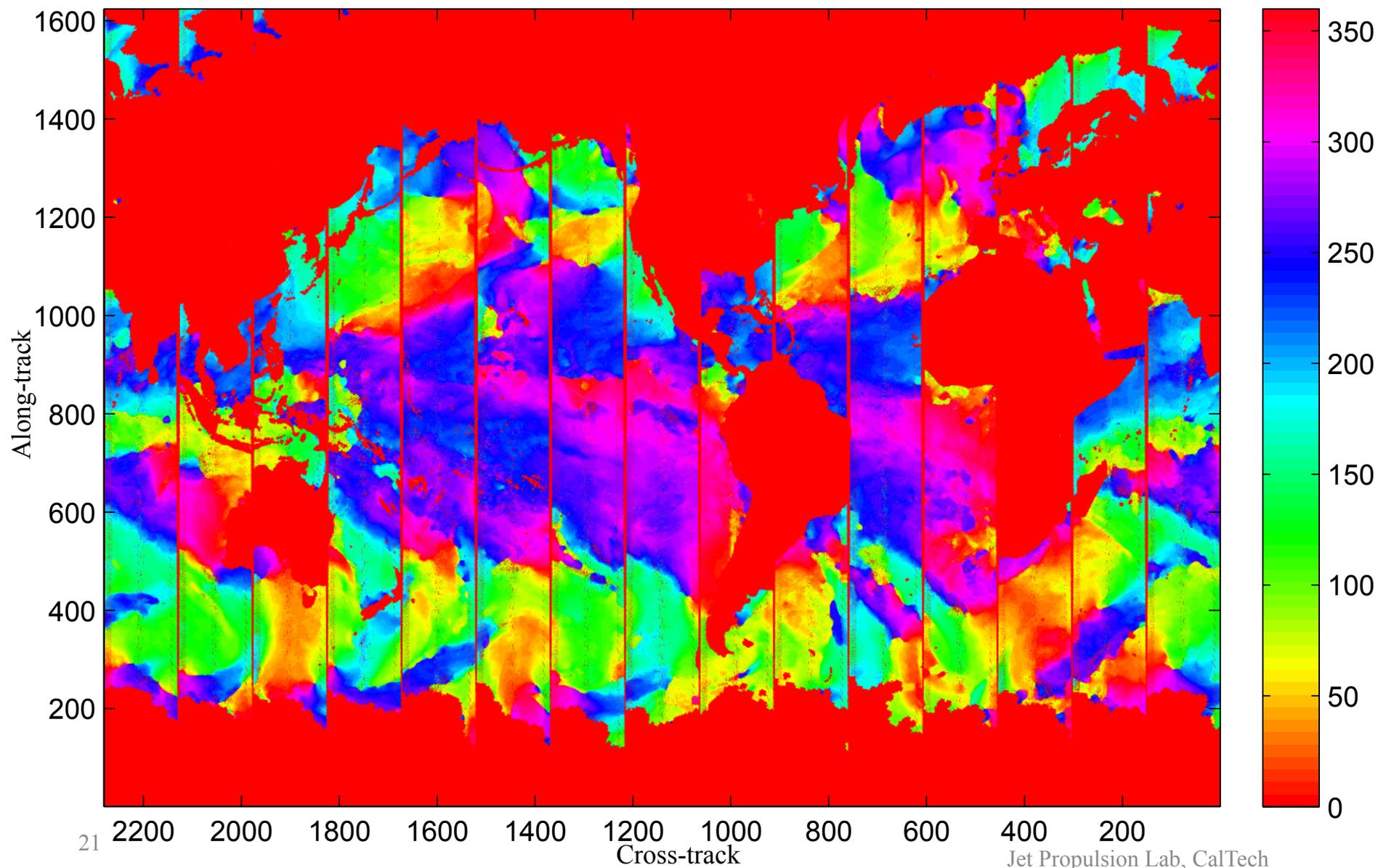
MAP Direction (deg.)

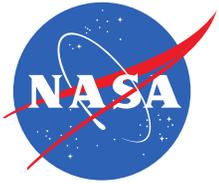




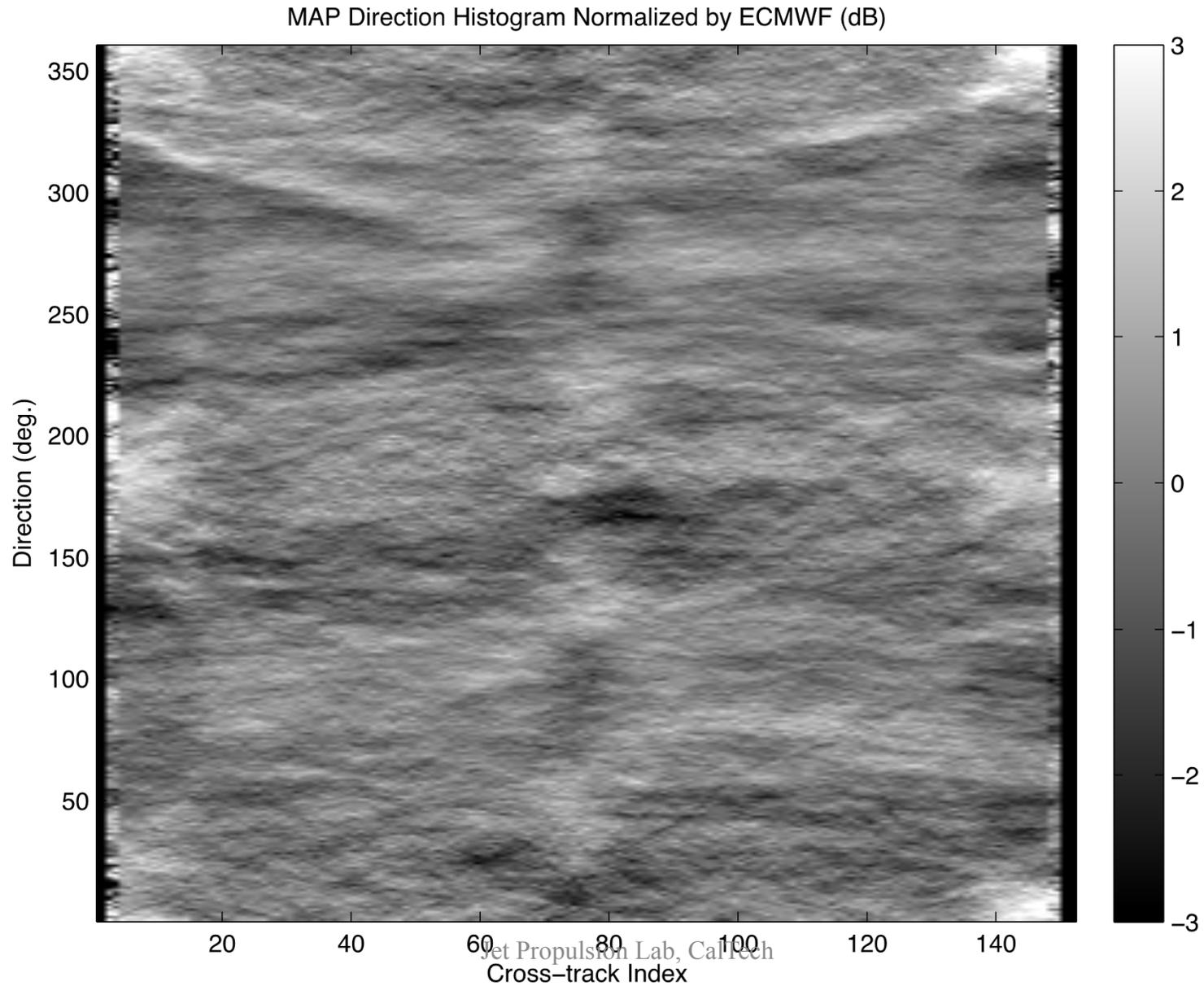
Examples: Tiled Revs

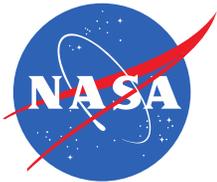
L2B12 Direction (deg.)





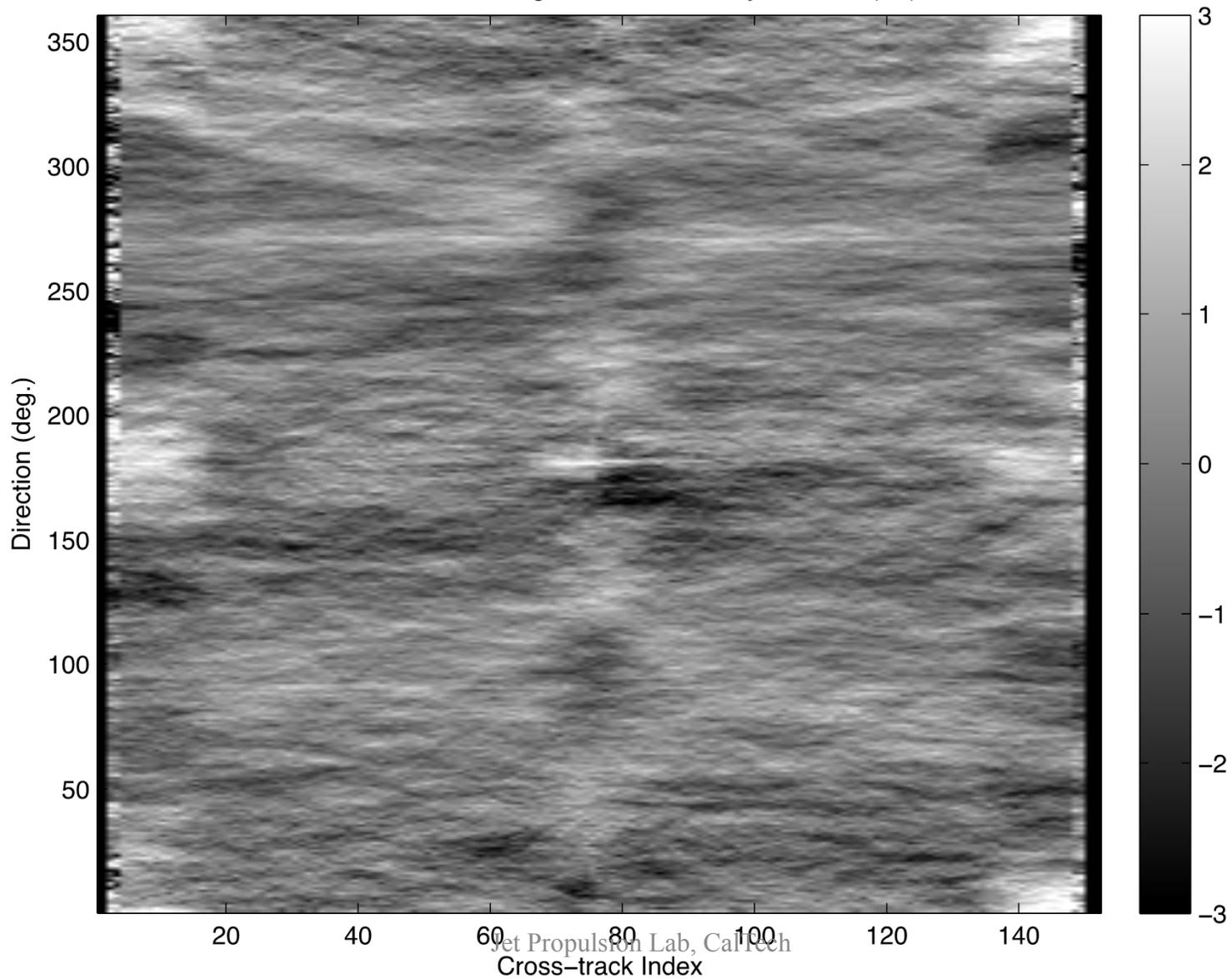
MAP Direction Histogram





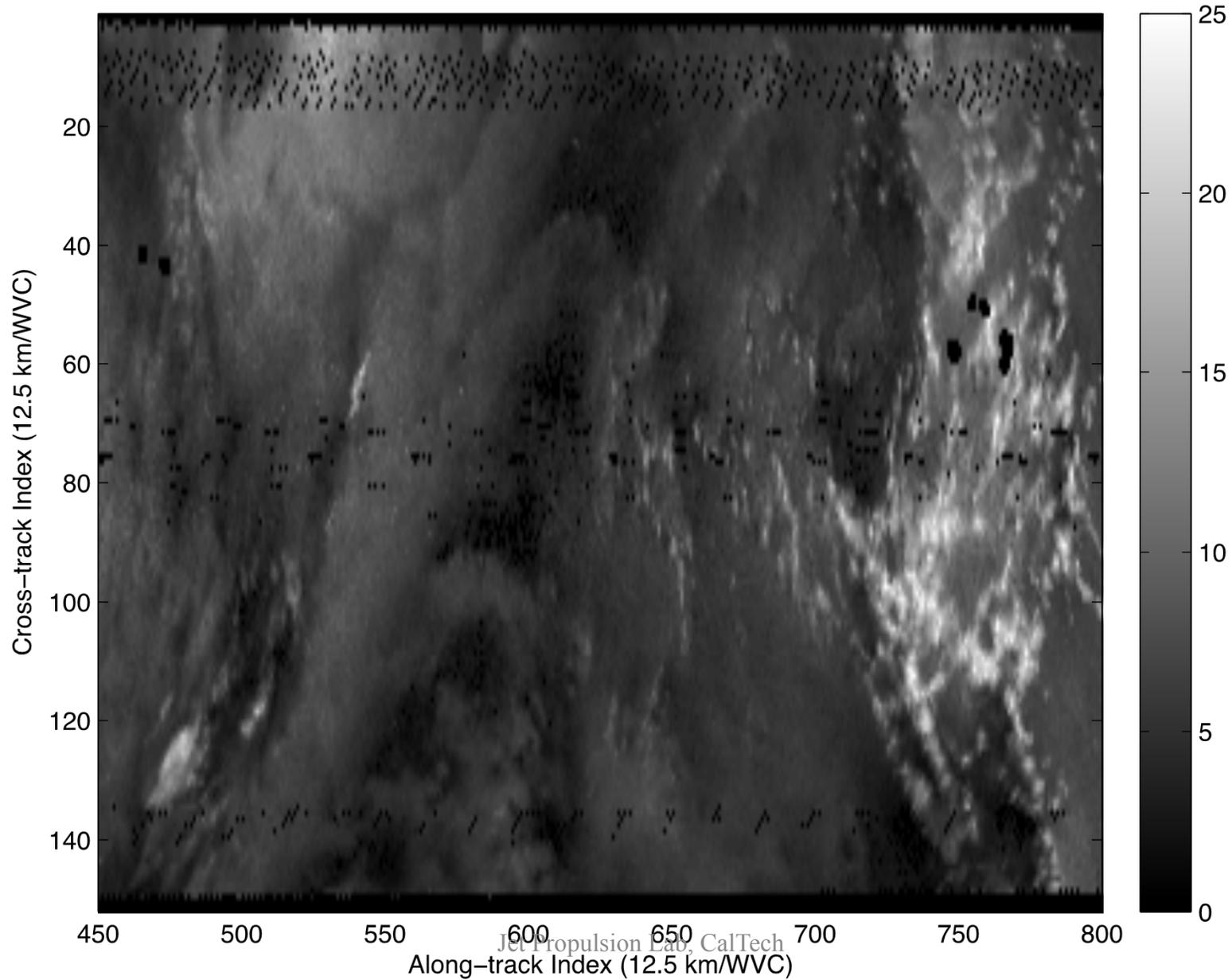
L2B12 DIRTH Direction Histogram

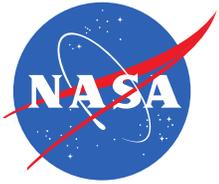
DIRTH Direction Histogram Normalized by ECMWF (dB)



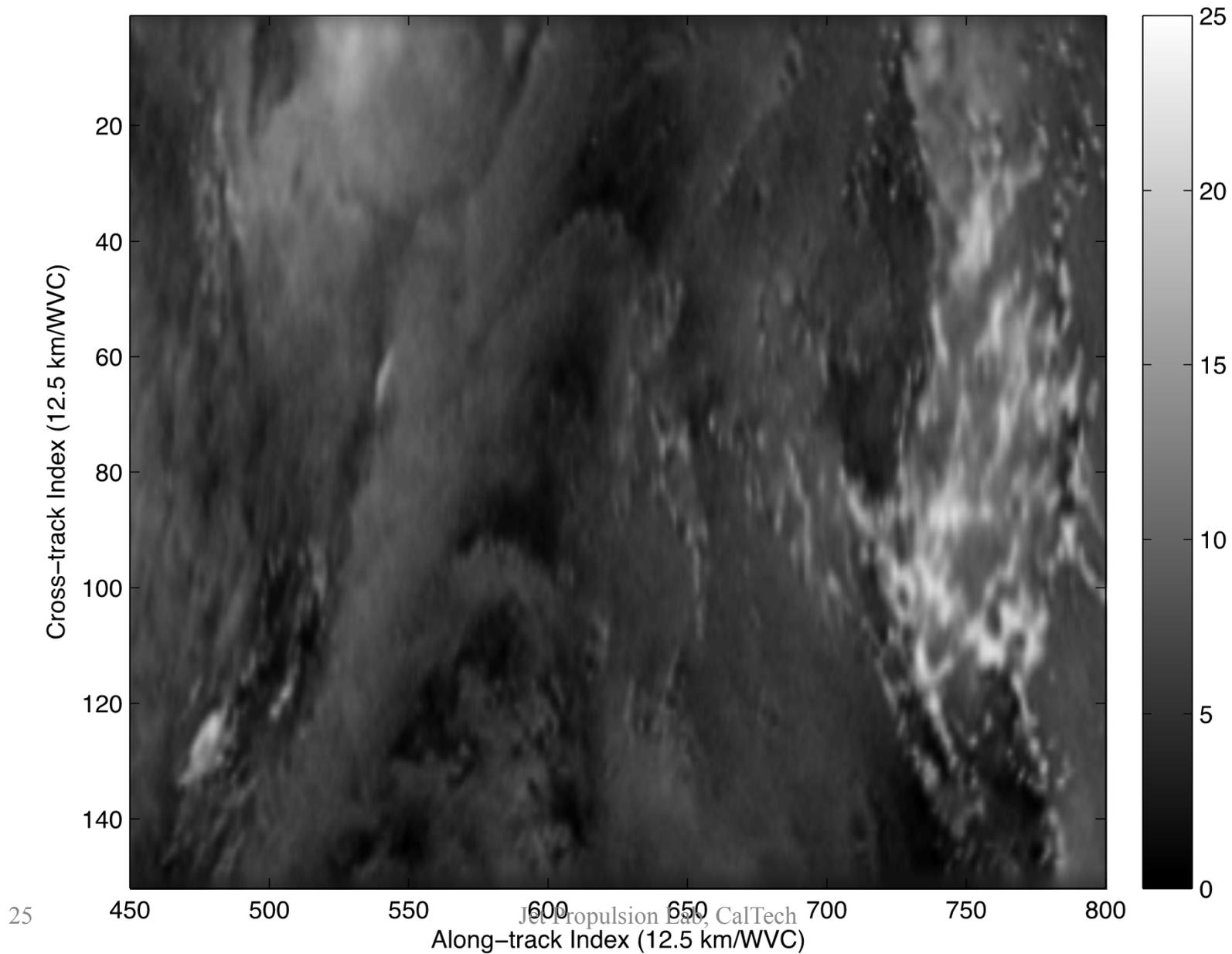


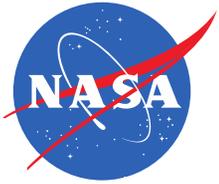
L2B12 DIRTH Speed



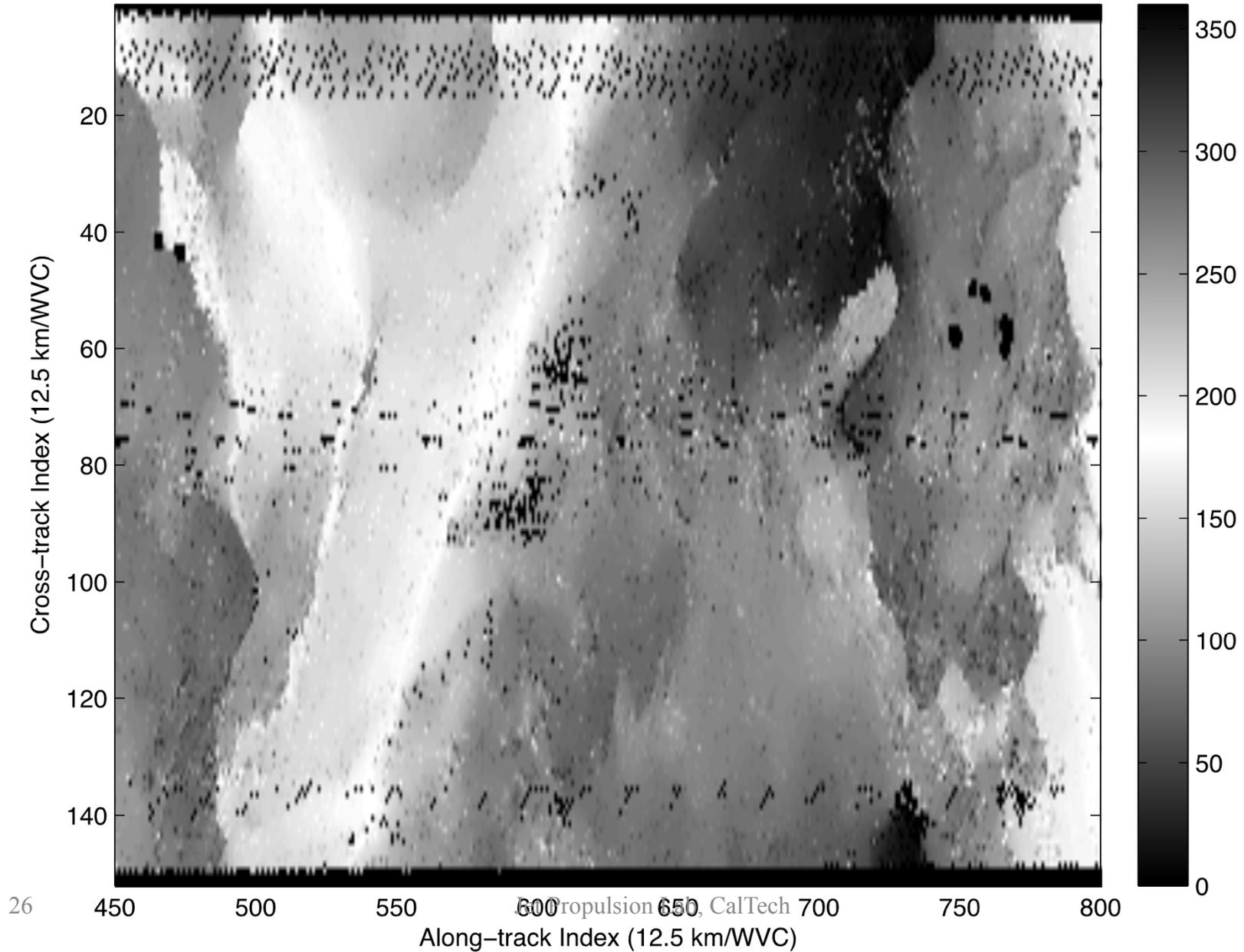


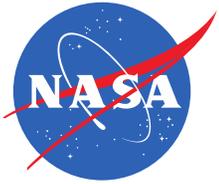
12.5km MAP Speed



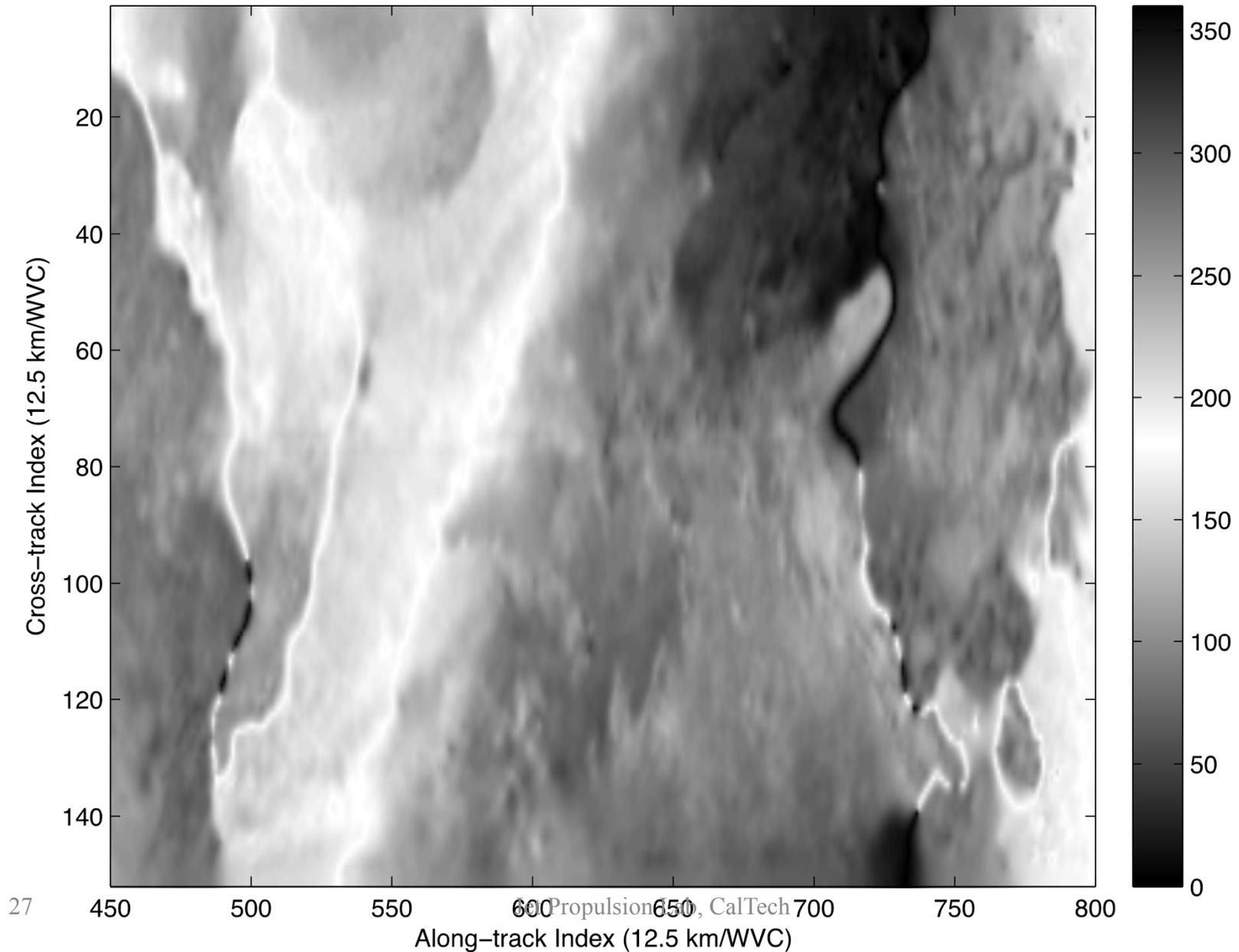


L2B12 DIRTH Direction



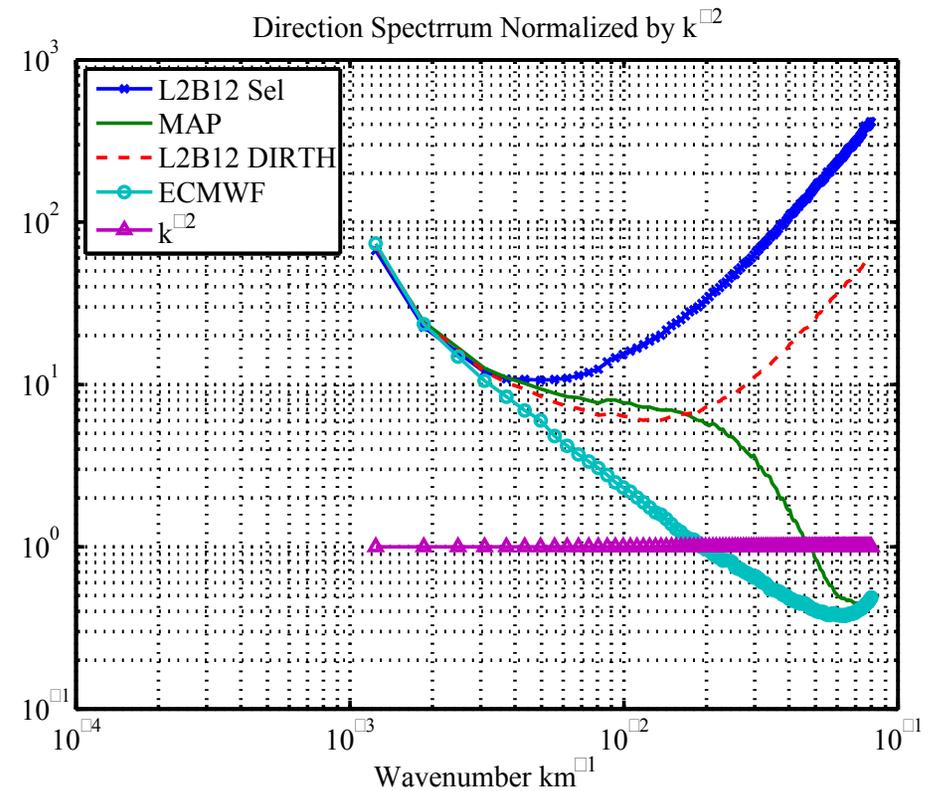
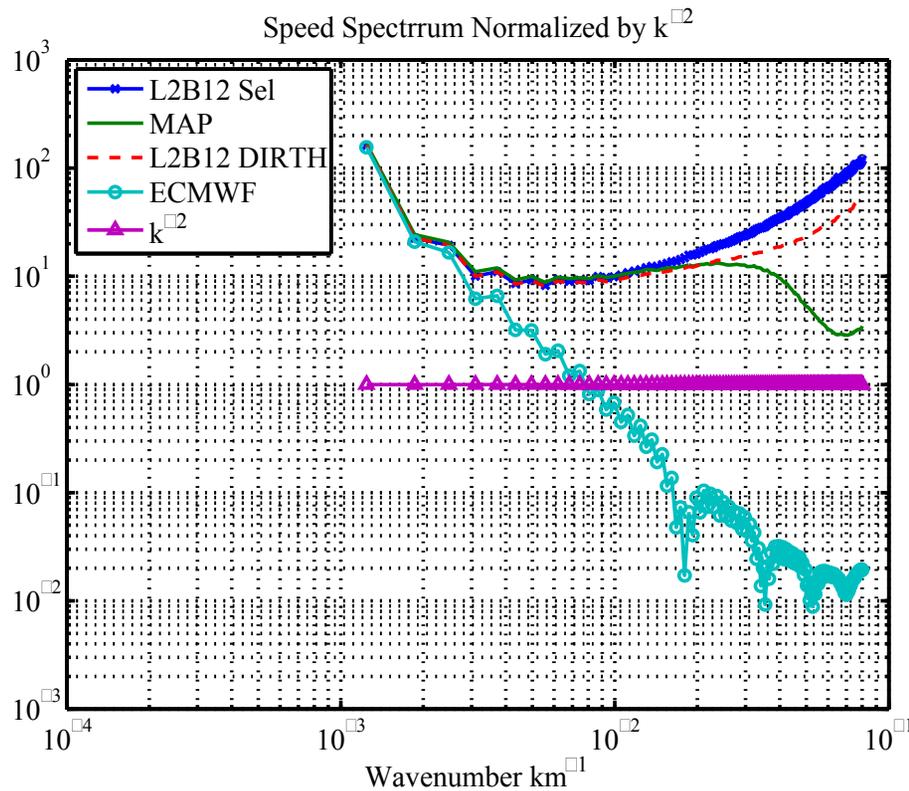


12.5km MAP Direction

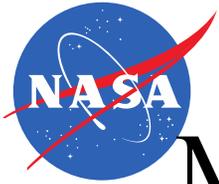




Analysis: Speed and Direction Spectra Normalized by k^{-2}



- Average speed resolution $\sim 25\text{-}33$ km
- Average direction resolution $\sim 50\text{km}$



MAP Estimation Implementation

- Maximize log of posterior (gradient search)

$$\frac{\partial}{\partial \vec{U}(x)} \log f(\vec{U}(x) | \vec{\sigma}_m^0) = \frac{\partial}{\partial \vec{U}(x)} [\log f(\vec{\sigma}_m^0 | \vec{U}(x)) + \log f(\vec{U}(x))]$$

$$\frac{\partial}{\partial U_i(x)} \log f(\vec{\sigma}_m^0 | \vec{U}(x)) = \sum_n -K_n A_n(x) \frac{\partial \text{gmf}_n(\vec{U}(x))}{\partial U_i(x)}$$

$$K_n = \left[\frac{(\sigma_n^0 - T_n(\vec{U}(x))) - (\alpha_n T_n(\vec{U}(x)) + \beta_n/2)}{R_{n,n}} + \frac{(\sigma_n^0 - T_n(\vec{U}(x)))^2 (\alpha_n T_n(\vec{U}(x)) + \beta_n/2)}{R_{n,n}^2} \right]$$

$$T_n(\vec{U}(x)) = \sum_x A_n(x) \text{gmf}_n(\vec{U}(x))$$